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# Nonlinearity and cross-country dependence of income inequality*

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**Abstract**

We use top income data and the newly developed regime switching Gaussian mixture vector autoregressive model to explain the dynamics of income inequality in developed economies within the last 100 years. Our results indicate that the process of income inequality consists of two equilibriums identifiable by high inequality, high income fluctuations and low inequality, low income fluctuations. Our results also show that income inequality in the U.S. is the driver of income inequality in other developed economies. Both economic and institutional changes emanating from the U.S. explain this dominance.

**Keywords:** top 1% income share, GMAR, multiple equilibria, developed economies.

**JEL Classification:** C32, C33, D30.

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# 1 Introduction

Income inequality has, once again, become a global topic. Estimates on the level of global income inequality vary,[1] but the share of the total income going to the top income earners has not been this high in many developed economies since the 1920's (Alvaredo *et al.* 2013). The history of the distribution of product is embodied by large fluctuations in the share of income massing at the top. According to Piketty (2014, p. 274) in the history of inequality "there have been many twists and turns and certainly no irrepressible, regular tendency toward a natural equilibrium". In a similar vein, Roine and Waldenström (2011) found global and country-specific break points from the top 1% income share series, which indicate that the process of income inequality could consists on different phases or equilibria. In this study we show that this is indeed the case: income inequality follows a regime switching process where higher inequality leads to higher variance in income shares and *vice versa*. We also show that changes in the income inequality in the U.S. have driven the inequality in other developed economies during the last 100 years.

The structure of income has varied quite heavily throughout the last century. In the period prior to the Second World War high incomes consisted mostly on returns to capital, which was the main reason for high inequality during that era (Piketty and Saez 2003; Piketty 2014). However, the biggest driver of the resurgence of income inequality in developed economies after 1970's has been the increasing share of high wages (Piketty 2014). Recent studies have uncovered that the variance of earnings has also been on the rise in developed economies during the same period (see, e.g., Daly and Valletta 2008; Gottschalk and Moffitt 2009; Beach *et al.* 2010). Although increasing variance of earning has occurred during a period marked by increasing income inequality, research on their relationship has been almost nonexistent.[2] Moreover, to our knowledge, there are no studies looking at the possible dependence of income inequality of an individual country on that of others. In this study, we are set to fill these gaps.

[1] See Sala-i-Martin (2002); Anand and Segal (2008); Milanovic (2015), among others.

[2] In the only study we could find, Beach *et al.* (2010) show that a rise in the total earnings variance in Canada after 1982 is mostly attributable to increase in overall inequality.

As argued by Piketty (2014), income inequality seems not to have been following any kind of mean reversing process (see above). This has been confirmed in many econometric studies, which have been unable to reject the unit root hypothesis in the autoregressive models for different measures of income inequality (e.g., Mocan 1999; Parker 2000; Jäntti and Jenkins 2010; Malinen 2012; Herzer and Vollmer 2013). However, this is a problematic result as the series of commonly used measures of income inequality, like the Gini index and the top income share, are bounded between 0 and 1 while the unit root series has a time-increasing variance. The breaks in the top 1% income share series identified by Roine and Waldenström (2011) could be one reason for the non-rejection of unit roots hypotheses. If breaks are actually shifts between different phases of income inequality identified by, e.g., different levels of variance, there would be no tendency towards a single equilibrium but shifts between multiple equilibria. A linear autoregressive model will be misspecified due to the observed jumps, whereas the so called trend-break models ignore the strong autocorrelation in the series.

We employ a newly developed Gaussian mixture autoregressive (GMAR) model studied in Kalliovirta, Meitz, and Saikkonen (2015) and its multivariate generalization, the Gaussian mixture vector autoregressive (GMVAR) model by Kalliovirta, Meitz, and Saikkonen (2014) to estimate the dynamic properties of income inequality. We use the GMAR and GMVAR models to identify the different regimes and autoregressive dynamics in the top income series, because they are able to model multiple equilibria. We analyze an updated version of the top 1% income share data ranging from the end of the 19th century to the beginning of the 21st century for six countries: Australia, Canada, France, Finland, Japan, and the USA.

We find that in all analyzed countries, the process of income inequality has consisted on two or three different regimes. Two of these regimes are also found to be common to all the aforementioned countries. Regimes are characterized by different means, or levels, and with different variances, or scales of variation. Moreover, our GMVAR results show that not only is the variance of income inequality highly dependent across countries, but that income inequality in the United States drives income inequality across our sample. Impulse response analysis reveals that the effect of the U.S. is especially strong in the high inequality, high income fluctuations regime, where all countries in our sample now reside. Both institutional and economic changes emanating from the U.S. explain this dominance.

The rest of the paper is organized as follows. Section 2 presents the data and the GMAR and GMVAR models. Section 3 presents the univariate and panel estimations of GMAR and GMVAR models. Section 4 discusses the economic implications of the estimation results and section 5 concludes.

# 2 Data and methods

The top 1% income share of population is used to proxy the income inequality. It is the only aggregate measure of income inequality that currently contain enough observations for meaningful testing of the time series properties of income inequality.[3] The data on top income shares is obtained from the World Top Income Database (WTID, Alvaredo *et al.* 2013). During the time of writing, WTID had long, continuous time series on six developing countries: Australia, Canada, Finland, France, Japan, and the U.S.[4] For these countries, the data on the top 1% income shares starts at the end of the 19th or the beginning of the 20th century. For other countries, the data either starts only after the Second World War and/or it has gaps extending to several years.

We assume that in each country the observed top 1% income share series follows a regime switching GMAR process. This assumption is reasonable, because regime switches are a natural way to adequately model jointly both the dynamic structure of these series and the breaks found in them. They especially allow for multiple equilibria, unlike linear AR models. Similar regime switching approach has been successfully used for example in Hamilton (1989) to model the U.S. business cycle. The Markov switching AR model of Hamilton (1989) and the constrained version of the GMAR model are closely connected; the latter is a special case of generalizations of the former. In the

[3]Leigh (2007) has also demonstrated that the top 1% income share series have a high correlation with other measures of income inequality, like the Gini index.

[4]For Japan, the observation from the year 1946 is missing, and it has been replaced with the average of the top 1% income share from years 1945 and 1947. For Canada the top 1% income share data is continued with the top 1% income share-LAD data after the year 2000. For Finland, the top 1% income share-tax data is continued with top 1% income share-IDS data after the year 1992.

Hamilton model the probability of a regime switch is constant, whereas in the GMAR model the change in regime is varying in time, which allows for more flexibility. However, the general flexibility of these regime switching models comes with a price: one has to be careful how to interpret them because, instead of a constant regime switching probability, an estimate of the probability of the series being in a certain regime is available for each time point. These estimated probabilities are henceforth referred as time-varying mixing weights.

The GMAR model has several advantageous properties compared to the more general Markov switching AR model or other nonlinear models. First, the GMAR model is more parsimonious, a considerable advantage when only yearly data for a hundred years or less are available. Second, the GMAR model is known to be stationary: It suffices that the usual stationarity condition of the conventional linear AR model is fulfilled in the regimes. Third, the stationary distribution of the GMAR model is known exactly. Thus, we are able to make direct comparisons to the unconditional moments of the original observations (as in Table 1), which can be interpreted as different equilibrium points. This would be unavailable if any other nonlinear model had been used, because the conditions for making the transition from the conditional to the unconditional distribution would be unknown. To learn more about the GMAR model and its competing nonlinear alternatives, see Kalliovirta, Meitz, and Saikkonen (2015).

To understand the joint behavior of the 1% income share series in all six countries, we employ the GMVAR model by Kalliovirta, Meitz, and Saikkonen (2014). In particular, this multivariate model is able to depict regime switches and dynamic structures common in all these six countries.

## 2.1 The univariate GMAR model

We assume that the top 1% income share series $y_t$ is generated by [5]

$$y_t = \sum_{m=1}^{M} s_{t,m}(\varphi_{m,0} + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \sigma_m \varepsilon_t),$$

[5] The AR coefficients are the same in all regimes. Thus, we consider a restricted GMAR model.

where unobservable random variables $s_{t,m}$ indicate the regimes $m = 1,...,M$ ($M = 2$ or 3). Parameters $\varphi_{m,0}$, $\varphi_1$, $\varphi_2$, and $\sigma_m$ fulfill restrictions: $\varphi(z) = 1 - \varphi_1 z - \varphi_2 z^2 \neq 0$ for $|z| \leq 1$ and $\sigma_m > 0$. For each $t$, exactly one of $s_{t,m}$ random variables takes the value one and others are equal to zero and random variables $\varepsilon_t$ are i.i.d. N(0,1). Further, variables $\varepsilon_t$ and $s_{t,m}$ are independent given the history of the observed series $y_t$, $\{y_{t-j}, j > 0\}$. The conditional probabilities $P(s_{t,m} = 1|y_{t-j}, j > 0) = \alpha_{m,t}$ are time-dependent mixing weights. So $\alpha_{m,t}$ yields the probability of the series being in regime $m$ at time point $t$. Or, the probability of the observation $y_t$ being generated by the AR(2) model of the $m$:th regime, $\varphi_{m,0} + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \sigma_m \varepsilon_t$, is equal to $\alpha_{m,t}$. Thus, these weights have to satisfy $\sum_{m=1}^{M} \alpha_{m,t} = 1$ for all $t$. In the GMAR model, the mixing weights depend on the past observations, the parameters $\varphi_{m,0}$, $\varphi_1$, $\varphi_2$, and $\sigma_m$, and additional weight parameters $\alpha_m > 0$, $\sum_{m=1}^{M} \alpha_m = 1$, according to

$$\alpha_{m,t} = \frac{\alpha_m \mathsf{n}_2(\boldsymbol{y}_{t-1}; \mu_m, \boldsymbol{\Gamma}_m)}{\sum_{n=1}^{M} \alpha_n \mathsf{n}_2(\boldsymbol{y}_{t-1}; \mu_n, \boldsymbol{\Gamma}_n)},$$

where $\boldsymbol{y}_{t-1} = (y_{t-1}, y_{t-2})$, $\mu_m = \varphi(1)^{-1}\varphi_{m,0}$, $\mathbf{1}_2 = (1,1)$, and

$$\mathsf{n}_2(\boldsymbol{y}_{t-1}; \mu_m, \boldsymbol{\Gamma}_m) = \{2\pi\}^{-1} det(\boldsymbol{\Gamma}_m)^{-1/2} \exp\left\{-\frac{1}{2}(\boldsymbol{y}_{t-1} - \mu_m \mathbf{1}_2)' \boldsymbol{\Gamma}_m^{-1} (\boldsymbol{y}_{t-1} - \mu_m \mathbf{1}_2)\right\}.$$

The symmetric, 2x2 Toeplitz matrix $\boldsymbol{\Gamma}_m$ is a function of parameters $\varphi_1$, $\varphi_2$ and $\sigma_m^2$ according to

$$vec(\boldsymbol{\Gamma}_m) = \left(I_{2^2} - \begin{bmatrix} \varphi_1 & \varphi_2 \\ 1 & 0 \end{bmatrix} \otimes \begin{bmatrix} \varphi_1 & \varphi_2 \\ 1 & 0 \end{bmatrix}\right)^{-1} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} \otimes \begin{bmatrix} 1 \\ 0 \end{bmatrix}\right) \sigma_m,$$

where $\otimes$ denotes the Kronecker product and *vec* the vectorization of a matrix. Notice that if $\varphi_2 = 0$, then matrix $\boldsymbol{\Gamma}_m$ simplifies to $\frac{\sigma_m^2}{1-\varphi_1^2}$ and the normal distributions above are univariate. Also, the restriction $\sum_{m=1}^{M} \alpha_m = 1$ reduces the number of free weight parameters $\alpha_m$ into $M-1$. Thus, if $M = 2$ we only have to estimate one weight parameter $\alpha_1$.

The stationary distribution of the GMAR model, $\sum_{m=1}^{M} \alpha_m \mathsf{n}_2(\boldsymbol{y}_{t-1}; \mu_m, \boldsymbol{\Gamma}_m)$, yields an alternative parameterization that employs $\mu_m$, $\boldsymbol{\varphi}$, $\gamma_{m,0}$, and $\alpha_m$, $m = 1,...,M$. We used this alternative parameterization in the univariate analysis and estimate the model parameters using maximum likelihood as suggested in Kalliovirta, Meitz, and Saikkonen (2015).

## 2.2 The multivariate GMVAR model

The GMAR model generalizes easily into the multivariate GMVAR model. We assume that the six dimensional top 1% income share series $\boldsymbol{y_t}$ is generated by

$$\boldsymbol{y_t} = \sum_{m=1}^{3} s_{t,m}\left(\phi_{m,0} + A_1\boldsymbol{y_{t-1}} + A_2\boldsymbol{y_{t-2}} + \Omega_m^{1/2}\boldsymbol{\varepsilon_t}\right),$$

where unobservable random variables $s_{t,m}$ indicate the regimes $m = 1,...,3$ and $\boldsymbol{\varepsilon_t}$ are i.i.d. N($\mathbf{0}$,$I_6$) random vectors.[6] Parameters $\phi_{m,0}$, $A_1$, $A_2$, and $\Omega_m$ fulfill the following conditions: $\det A(z) \neq 0$ for $|z| \leq 1$ with $A(z) = I_6 - A_1 z - A_2 z^2$ and covariance matrix $\Omega_m$ is positive definite. The random variables $\boldsymbol{\varepsilon_t}$ and $s_{t,m}$ are independent given $\{\boldsymbol{y_{t-j}}, j > 0\}$. For each $t$, the variables $s_{t,m}$ are defined as in the univariate case meaning that exactly one of them takes the value one and others are equal to zero. The time-dependent mixing weights $\alpha_{m,t}$ are the conditional probabilities $P(s_{t,m} = 1|\boldsymbol{y_{t-j}}, j > 0)$. Also, the probability of the observation $\boldsymbol{y_t}$ being generated by the VAR(2) model of the $m$:th regime, $\phi_{m,0} + A_1\boldsymbol{y_{t-1}} + A_2\boldsymbol{y_{t-2}} + \Omega_m^{1/2}\boldsymbol{\varepsilon_t}$, is equal to $\alpha_{m,t}$. Thus, similar to GMAR model these weights satisfy $\sum_{m=1}^{3}\alpha_{m,t} = 1$ for all $t$. In the GMVAR model, the mixing weights depend on the past observations, the parameters $\phi_{m,0}$, $A_1$, $A_2$, and $\Omega_m$, and additional weight parameters $\alpha_m > 0$, $\sum_{m=1}^{3}\alpha_m = 1$, according to

$$\alpha_{m,t} = \frac{\alpha_m \mathsf{n}_{12}\left(\boldsymbol{Y}_{t-1};\boldsymbol{\mu}_m,\boldsymbol{\Gamma}_m\right)}{\sum_{n=1}^{3}\alpha_n \mathsf{n}_{12}\left(\boldsymbol{Y}_{t-1};\boldsymbol{\mu}_n,\boldsymbol{\Gamma}_n\right)},$$

where $\boldsymbol{Y}_{t-1} = \left(\boldsymbol{y}'_{t-1},\boldsymbol{y}'_{t-2}\right)'$, $\boldsymbol{\mu}_m = A(1)^{-1}\phi_{m,0}$, $\mathbf{1}_2 = (1,1)$, and

$$\mathsf{n}_{12}\left(\boldsymbol{Y}_{t-1};\boldsymbol{\mu}_m,\boldsymbol{\Gamma}_m\right) = \{2\pi\}^{-6}\,det(\boldsymbol{\Gamma}_m)^{-1/2}\exp\left\{-\frac{1}{2}\left(\boldsymbol{Y}_{t-1} - \mathbf{1}_2\otimes\boldsymbol{\mu}_m\right)'\boldsymbol{\Gamma}_m^{-1}\left(\boldsymbol{Y}_{t-1} - \mathbf{1}_2\otimes\boldsymbol{\mu}_m\right)\right\}.$$

The symmetric, 12x12 Toeplitz matrix $\boldsymbol{\Gamma}_m$ is a function of matrices $A_1$, $A_2$, and $\Omega_m$, according to

$$vec\left(\boldsymbol{\Gamma}_m\right) = \left(I_{12^2} - \begin{bmatrix} A_1 & A_2 \\ I_6 & \mathbf{0} \end{bmatrix} \otimes \begin{bmatrix} A_1 & A_2 \\ I_6 & \mathbf{0} \end{bmatrix}\right)^{-1} \left(\begin{bmatrix} I_6 \\ \mathbf{0} \end{bmatrix} \otimes \begin{bmatrix} I_6 \\ \mathbf{0} \end{bmatrix}\right) vec\left(\Omega_m\right),$$

where $\otimes$ denotes the Kronecker product and $vec$ the vectorization of a matrix. The stationary distribution of the GMVAR model, $\sum_{m=1}^{3}\alpha_m \mathsf{n}_{12}\left(\boldsymbol{Y}_{t-1};\boldsymbol{\mu}_m,\boldsymbol{\Gamma}_m\right)$, yields an alternative parameterization that employs $\boldsymbol{\mu}_m$, $A_1$, $A_2$, $\boldsymbol{\Gamma}_m$, and $\alpha_m$, $m = 1,2,3$. We report

[6]The AR coefficient matrices are the same in all regimes. Thus, we consider a restricted GMVAR model.

these alternative parameterizations also in the multivariate analysis and estimate the model parameters using maximum likelihood as suggested in Kalliovirta, Meitz, and Saikkonen (2014).

# 3 Results

## 3.1 Univariate model

As a starting point for the analysis of each series, we estimated linear Gaussian AR models. Residual diagnostics (not reported) rejected these models due to non-normality and conditional heteroskedasticity, which is a clear indication of nonlinearity in the modeled series. We also tested the top 1% income series with a STAR model and it rejects the linearity hypotheses in all countries.[7] Table 1 presents the properties of the original series and the estimation results for GMAR models that pass the quantile residual diagnostics of Kalliovirta (2012).[8] Clearly, the original series are persistent in all six countries, and the variances are also highly fluctuating from around 24 in Japan to around 5 in Australia. GMAR model finds two regimes in the top 1% income series in all countries except Australia, where three regimes are found. The series of France, Japan, and the USA require two lags in the GMAR model, whereas one lag is enough for the other three countries.

The regimes of GMAR models seem to be marked with quite clear and similar characteristics in all countries. In one regime, the mean and variance of the top 1% income series are clearly higher, whereas in the other regime both are considerably lower. So, in

[7]Results are available on request.

[8]The accuracy of the mean, variance, and weight parameter estimates suffer from the lack of data. Testing the significance of the mixing weights is a theoretically highly demanding nonstandard testing problem common to all regime switching models like the STAR and Markov switching models (see Kalliovirta, Meitz, and Saikkonen (2015) for more explanation), and it has not been solved yet for GMAR models. For the same reason one cannot test the equality of the means or variances simply by comparing their estimates and standard errors, because these parameters are closely connected to the time varying mixing weights. Further, testing the equality of means and variances jointly would again lead to the nonstandard testing problem. However, we can test them separately. For example, in the income series of Canada the LR tests for equality of means has p-value 0.31 and equality of variances has p-value $< 10^{-12}$. The quantile residual diagnostics indicate that the model with equal means describes inadequately the autocorrelation of the series. Thus, the model reported in the table is chosen.

For this reason, we base the model specification on the theoretically appropriate quantile residual diagnostics that supports nonlinearity over linearity in all six models. Further, information criteria like AIC and BIC (not reported) clearly indicate that the nonlinear models are superior. More details on the estimated models and residual diagnostics are available upon request.

Table 1: Estimation results on the top 1% income share

| | Australia | Canada | Finland | France | Japan | USA |
|---|---|---|---|---|---|---|
| Original data | | | | | | |
| First autocorrelation | 0.94 | 0.96 | 0.95 | 0.96 | 0.98 | 0.95 |
| mean | 8.2 | 11.4 | 8.8 | 10.8 | 12.2 | 12.8 |
| variance | 4.5 | 8.8 | 9.5 | 14.9 | 24.4 | 14.7 |
| | | | | | | |
| GMAR model | | | | | | |
| autocorrelation ($\varphi_1$) | 0.90 | 0.95 | 0.94 | 1.11 | 1.33 | 1.14 |
| | (0.04) | (0.03) | (0.03) | (0.11) | (0.08) | (0.10) |
| autocorrelation ($\varphi_2$) | | | | -0.16 | -0.42 | -0.24 |
| | | | | (0.12) | (0.09) | (0.10) |
| mean 1 ($\mu_1$) | 4.8 | 9.6 | 4.9 | 8.4 | 8.1 | 8.2 |
| | (0.1) | (0.8) | (0.5) | (0.4) | (0.3) | (0.3) |
| mean 2 ($\mu_2$) | 6.0 | 14.3 | 7.9 | 15.5 | 16.7 | 15.1 |
| | (0.4) | (4.4) | (1.6) | (2.2) | (1.5) | (1.2) |
| mean 3 ($\mu_3$) | 9.1 | | | | | |
| | (1.0) | | | | | |
| variance 1 ($\gamma_1$) | 0.01 | 1.4 | 0.5 | 0.6 | 0.6 | 0.2 |
| | (0.01) | (0.7) | (0.3) | (0.3) | (0.2) | (0.1) |
| variance 2 ($\gamma_2$) | 0.3 | 15.2 | 4.5 | 11.3 | 12.7 | 6.6 |
| | (0.1) | (9.6) | (2.1) | (5.8) | (5.2) | (2.5) |
| variance 3 ($\gamma_3$) | 2.9 | | | | | |
| | (1.3) | | | | | |
| $\alpha_1$ | 0.08 | 0.95 | 0.22 | 0.42 | 0.62 | 0.17 |
| | (0.1) | (0.08) | (0.2) | (0.3) | (1.4) | (0.3) |
| $\alpha_2$ | 0.47 | | | | | |
| | (0.2) | | | | | |
| years | 1921-2010 | 1920-2010 | 1920-2009 | 1915-2009 | 1886-2010 | 1914-2012 |

Standard errors (in parentheses) are calculated using the estimated Hessian.

these countries, income inequality has consisted on two notably different regimes. First one is a low income inequality, low income fluctuations regime and the second is a high income inequality, high income fluctuations regime. Even though the Australian series has three regimes, the same characteristics are found in them.

Further, our analysis points out that the evolution of the top 1% income series cannot be modeled adequately using a linear model. The nonlinear structure of the series with different constants and variances between regimes increases the autocorrelation observed in the original series. This indicates that, although the dynamics of income inequality can be *approximated* with a stochastic trend, i.e., with a unit root process, it may not be its true form.

Figure 1 presents the top 1% income shares and the estimated time-dependent mixing weights for the above mentioned six countries. In all six subfigures the mixing weights $\hat{\alpha}_{1,t}$ (dashed line) (or $\hat{\alpha}_{2,t}$ (dotted line) in the subfigure for Australia) are given on the right axis while the share of total income earned by the top 1% of the income earners (solid line) is given on the left axis.

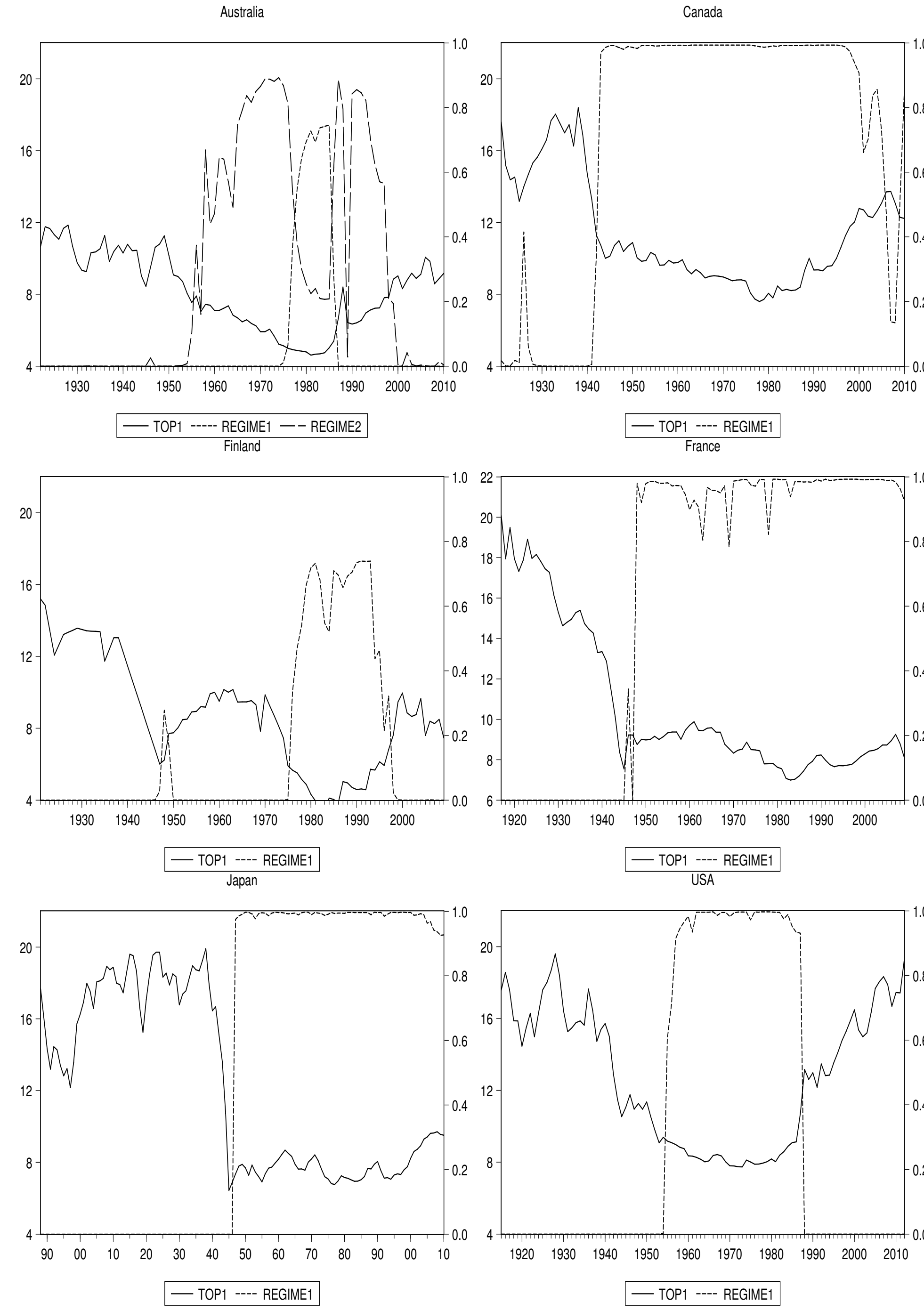


Figure 1. Top 1% income shares and the time-dependent mixing weights for Australia, Canada, Finland, France, Japan and the USA based on the univariate GMAR models.

In Australia, the probability that income inequality is in the third regime is above 90% until 1955. In 1955, the probability of the second regime begins to rise. Transition from the second regime into the first regime happens around 1975 and back into the second regime in 1987. In 1999, the series moves back into the third regime. In Canada, France and Japan, income inequality switches the regime right after the Second World War. The probability that the income inequality series is in the first regime increases to 99% in Canada in 1944, to 98% in France in 1948, and to 98% in Japan in 1948. In Finland, the probability of income inequality being in the first regime increases to 33% in 1976 and decreases below 2% in 1998. In the USA, the probability that income inequality is in the first regime increases to 61% in 1955. After 1988, the probability of the second regime is 100%.

The results based on GMAR models imply that many of the structural breaks found by Roine and Waldenström (2011) are points, where the series of income inequality changes regime and the characteristics of the series change in terms of means and variances. We find the following correspondences between the breaks of Roine and Waldenström and the regime switches: 1) in Australia, the regime change in 1987 corresponds the structural break in the country-specific series in 1985; 2) in Canada, the country-specific break point in 1994 corresponds the probability of second regime beginning to increase in 1998; 3) in Finland, the probability of income inequality being in the first regime increases into 73% in 1981 which corresponds to the break in post-war data on Nordic countries, and the probability of second regime rices over 68% in 1997, which corresponds to the country-specific break in 1997; 4) in Canada, France, and Japan, the changes from the second regime into the first regime correspond to the global trend break point in 1946; and 5) in Australia and USA, the changes in regime around 1955 and 1987 correspond to the common structural break in 1953 and the common post-war break in Anglo-Saxon countries in 1987.

## 3.2 Multivariate, panel data model

Next we combine the six individual series into a panel over the years 1921 and 2009 to find out whether the regime switches and other dynamics in these series move in tandem. The GMVAR model that passes quantile residual diagnostics has three regimes and the VAR structure is common to all regimes and has the maximum of two lags. [9]

We report the estimated GMVAR model component by component to make comparisons easy with the estimated univariate models and report the estimated Hessian based standard errors in parentheses below. The estimated weight parameters for the first and second regimes in the GMVAR model are $\hat{\alpha}_1 = \underset{(0.28)}{0.14}$ and $\hat{\alpha}_2 = \underset{(0.28)}{0.85}$. Note that these estimates also yield the unconditional probabilities $P(s_{t,1} = 1) = 0.14$, $P(s_{t,2} = 1) = 0.85$, and $P(s_{t,3} = 1) = 0.01$. We denote the $i$th element of vector $\hat{\Omega}_2^{1/2}\boldsymbol{\varepsilon}_t$ with $u_{t,i}$ and report separately the estimated covariance matrix $\hat{\Omega}_2$, because it is not diagonal like $\hat{\Omega}_1$. The third regime is added to allow the constants of France and Japan to change within the second regime so there is no need for the third covariance matrix. Based on LR statistics, we restrict the variance parameter for Finland to be the same in both regimes. The top 1% income share series of Australia, Canada, Finland, France, Japan, and the USA follow:

$$
\begin{aligned}
y_{t,Aus} &= \underset{(0.04)}{0.93} y_{t-1,Aus} + \underset{(0.04)}{0.02} y_{t-1,USA} \\
&\quad + s_{t,1}\left(\underset{(0.27)}{0.23} + \sqrt{\underset{(0.02)}{0.08}}\,\varepsilon_{t,Aus}\right) + (1 - s_{t,1})\left(\underset{(0.44)}{0.28} + u_{t,1}\right), \\
y_{t,Can} &= \underset{(0.11)}{1.00} y_{t-1,Can} + \underset{(0.05)}{0.11} y_{t-1,USA} - \underset{(0.10)}{0.15} y_{t-2,Can} \\
&\quad + s_{t,1}\left(\underset{(0.28)}{0.35} + \sqrt{\underset{(0.02)}{0.07}}\,\varepsilon_{t,Can}\right) + (1 - s_{t,1})\left(\underset{(0.46)}{0.17} + u_{t,2}\right), \\
y_{t,Fin} &= \underset{(0.03)}{0.91} y_{t-1,Fin} + \underset{(0.04)}{0.07} y_{t-1,USA} \\
&\quad + s_{t,1}\left(\underset{(0.27)}{0.13} + \sqrt{\underset{(0.07)}{0.47}}\,\varepsilon_{t,Fin}\right) + (1 - s_{t,1})\left(\underset{(0.41)}{-0.23} + u_{t,3}\right), \\
y_{t,Fra} &= \underset{(0.03)}{0.88} y_{t-1,Fra} + \underset{(0.02)}{0.06} y_{t-1,USA} \\
&\quad + s_{t,1}\left(\underset{(0.23)}{0.54} + \sqrt{\underset{(0.02)}{0.07}}\,\varepsilon_{t,Fra}\right) + s_{t,2}\left(\underset{(0.30)}{0.19} + u_{t,4}\right) + s_{t,3}\left(\underset{(0.49)}{0.83} + u_{t,4}\right),
\end{aligned}
$$

[9] Similar to the univariate models, the accuracy of mean, variance, and mixing weights estimates suffer from the lack of data. One may suspect that there are several redundant mean and variance parameters based on their standard errors. However, the testing of their equivalence has to be based on LR tests (e.g. a LR test for equality of means in regimes 1 and 2 for France has p-value 0.002), and hypotheses that contain unidentified nuisance parameters lead again to the nonstandard testing problems common to all regime switching models. Thus, we base model selection on the information criteria and theoretically appropriate quantile residual diagnostics, which strongly support the GMVAR model. Note also that compared to the univariate case the joint modeling has led to more efficient parameter estimates for the regime variances.

$$
\begin{aligned}
y_{t,Jpn} &= \underset{(0.09)}{1.22} y_{t-1,Jpn} + \underset{(0.03)}{0.13} y_{t-1,USA} - \underset{(0.08)}{0.33} y_{t-2,Jpn} \\
&\quad + s_{t,1}\left(\underset{(0.28)}{-0.21} + \sqrt{\underset{(0.01)}{0.04}}\varepsilon_{t,Jpn}\right) + s_{t,2}\left(\underset{(0.46)}{-0.75} + u_{t,5}\right) + s_{t,3}\left(\underset{(0.62)}{-0.16} + u_{t,5}\right).
\end{aligned}
$$

$$
\begin{aligned}
y_{t,USA} &= \underset{(0.10)}{1.21} y_{t-1,USA} - \underset{(0.10)}{0.28} y_{t-2,USA} \\
&\quad + s_{t,1}\left(\underset{(0.37)}{0.55} + \sqrt{\underset{(0.01)}{0.03}}\varepsilon_{t,USA}\right) + (1 - s_{t,1})\left(\underset{(0.67)}{0.90} + u_{t,6}\right).
\end{aligned}
$$

The autoregressive dynamics within countries remain very similar to what is found in the univariate models. However, the first lag of the top 1% income share in the USA affects the autoregressive dynamics of all countries, although the effect is weak in Australia. The positive coefficients indicate that an increase (decrease) in the income inequality in the USA leads to an increase (decrease) in the income inequality in other countries. Thus, the changes in the income inequality in the USA are exported to countries across our sample.

The mean vectors of the stationary distribution, solved using $\boldsymbol{\mu}_m = A(1)^{-1}\phi_{m,0}$, are:

$$
\boldsymbol{\mu}_1 = \begin{bmatrix} \mu_{1,Aus} \\ \mu_{1,Can} \\ \mu_{1,Fin} \\ \mu_{1,Fra} \\ \mu_{1,Jpn} \\ \mu_{1,USA} \end{bmatrix} = \begin{bmatrix} \underset{(0.6)}{6.0} \\ \underset{(0.5)}{9.0} \\ \underset{(1.2)}{7.5} \\ \underset{(0.4)}{8.6} \\ \underset{(0.6)}{7.8} \\ \underset{(0.5)}{8.5} \end{bmatrix}, \quad \boldsymbol{\mu}_2 = \begin{bmatrix} \underset{(1.8)}{8.6} \\ \underset{(1.9)}{12.0} \\ \underset{(1.8)}{7.6} \\ \underset{(1.2)}{8.5} \\ \underset{(2.5)}{9.2} \\ \underset{(2.1)}{14.0} \end{bmatrix}, \quad and \quad \boldsymbol{\mu}_3 = \begin{bmatrix} \mu_{2,Aus} \\ \mu_{2,Can} \\ \mu_{2,Fin} \\ \underset{(2.0)}{13.7} \\ \underset{(3.2)}{14.3} \\ \mu_{2,USA} \end{bmatrix}.
$$

The mean vectors of the stationary distribution of the GMVAR model have roughly the same values as what is found in the univariate GMAR models. The differences are found in Australia, where the third, lowest mean regime found in the univariate GMAR model becomes redundant, and in Finland, where the mean value of the top 1% income share of low regime has increased significantly.

### 3.2.1 Time-dependent mixing weights

Figure 2 depicts the top 1% income shares and the estimated time-dependent mixing weights for the above mentioned six countries. In all subfigures the mixing weights $\hat{\alpha}_{1,t}$ (dashed line) (or $\hat{\alpha}_{2,t}$ (dotted line) in the subfigures for France and Japan) are given

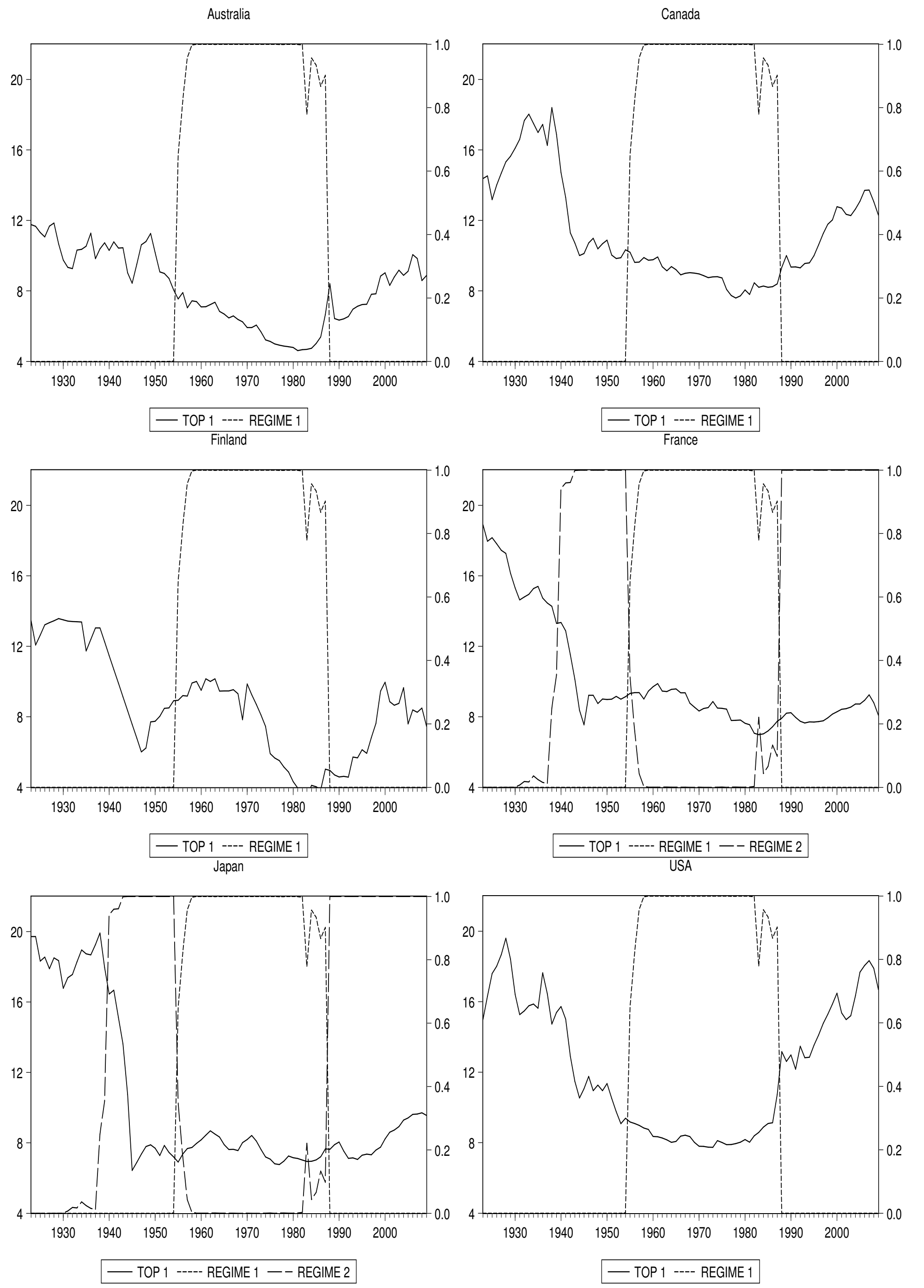


Figure 2. Top 1% income shares and the time-dependent mixing weights for Australia, Canada, Finland, France, Japan and the USA based on the GMVAR model.

on the right axis while the share of total income earned by the top 1% of the income earners (solid line) is given on the left axis. At the beginning of the period the series of France and Japan are in the third regime and the other series in the second regime with the probability of 100%. Both these regimes have high mean and high variance. France and Japan change to the second, low inequality regime around 1940.[10] Between 1955 and 1987, all the series are in the first regime with the probability of 99 %.[11] This first regime has low mean and low variance. After 1988 the probability of the second regime is above 82% for all countries indicating that income distribution has returned to the high inequality, high income fluctuations regime. The regime changes common to all six countries in the multivariate model in 1953 and in 1987 are the same ones observable in the univariate model for the USA. Thus, this further illustrates the significant effect the U.S. series has on the dynamics for all the series in the multivariate model.

#### 3.2.2 Details of the regime change

The striking similarity of the changes in regimes in the univariate GMAR model for the USA and in the multivariate GMVAR model imply that changes between regimes in the 1950s and in the 1980s are driven by the income inequality in the USA. We now explain why this holds in more detail. In the Appendix we present contour plots of the estimated mixing weights of the GMVAR model. They show that a change in the conditional variance in the U.S. series causes the regime to change in the multivariate model both in the 1950s and in the end of the 1980s. That is, changes in income inequality of the U.S. have driven regime changes of inequality across our sample in the 1950s and in the 1980s. Detailed analysis and description of the analysis of regime change is presented in the Appendix.

#### 3.2.3 Regime specific covariances

The different behavior of the series within regimes is also visible in the covariance matrices. In the first regime, where the means and variances are low, the covariance matrix $\hat{\Omega}_1$ is diagonal. So, the shocks of the components do not affect each other, and in each country the variation is country-specific. The estimated covariance matrix of the

[10]This is mostly due to fall in capital incomes caused by shocks, i.e, depression and wars (see, Piketty and Saez (2006); Piketty (2014)). In Japan there was also a major political regime shift in 1947, when the Empire of Japan was dissolved.

[11]The global break points found by Roine and Waldenström (2011) were in 1945 and in 1980.

second (and the third) regime

$$\hat{\Omega}_2 = \begin{bmatrix} \underset{(0.09)}{0.50} & \underset{(0.07)}{0.13} & 0 & \underset{(0.05)}{0.12} & \underset{(0.07)}{0.16} & \underset{(0.09)}{0.24} \\ \underset{(0.07)}{0.13} & \underset{(0.10)}{0.54} & 0 & 0 & \underset{(0.07)}{0.14} & \underset{(0.10)}{0.17} \\ 0 & 0 & \underset{(0.07)}{0.47} & 0 & 0 & 0 \\ \underset{(0.05)}{0.12} & 0 & 0 & \underset{(0.06)}{0.30} & \underset{(0.06)}{0.22} & 0 \\ \underset{(0.07)}{0.16} & \underset{(0.07)}{0.14} & 0 & \underset{(0.06)}{0.22} & \underset{(0.11)}{0.57} & 0 \\ \underset{(0.09)}{0.24} & \underset{(0.10)}{0.17} & 0 & 0 & 0 & \underset{(0.18)}{0.91} \end{bmatrix}$$

shows that excepting Finland the components affect each other through shocks.[12] In the second (and the third) regime, the means and variances are high and shocks in one country will affect the future values in the other countries. To make the strength of the dependence between countries easier to interpret, we also report the corresponding correlation matrix

$$\begin{bmatrix} 1 & \underset{(0.13)}{0.26} & 0 & \underset{(0.12)}{0.32} & \underset{(0.12)}{0.30} & \underset{(0.12)}{0.36} \\ \underset{(0.13)}{0.26} & 1 & 0 & 0 & \underset{(0.12)}{0.24} & \underset{(0.13)}{0.24} \\ 0 & 0 & 1 & 0 & 0 & 0 \\ \underset{(0.12)}{0.32} & 0 & 0 & 1 & \underset{(0.10)}{0.53} & 0 \\ \underset{(0.12)}{0.30} & \underset{(0.12)}{0.24} & 0 & \underset{(0.10)}{0.53} & 1 & 0 \\ \underset{(0.12)}{0.36} & \underset{(0.13)}{0.24} & 0 & 0 & 0 & 1 \end{bmatrix}.$$

Although the effect of the U.S. on the top 1% income series of Australia is weak in terms of the autoregressive dynamics (see Section 3.2), the effect is significant in both directions (correlation 0.36) in the second regime through the shocks. The strongest dependence between shocks is observed for France and Japan, where correlation is 0.53. Further, the income inequality between these two and between the Anglo-Saxon countries Australia, Canada and USA are connected through shocks.

### 3.2.4 Impulse response analysis

To gain better understanding about the dynamical system in the estimated GMVAR model, we compute the regime specific orthogonal impulse responses of the top 1% income shares of all countries to a unit shock in the U.S. series. We also include a linear

[12] The variance of the top 1% income share of the second regime in Finland is identical to that in the first regime (see the autoregressive dynamics in section 3.2). However, the conditional variance of Finland changes due to the regime structure.

VAR model in the analysis to obtain more comparison.[13] We employ the orthogonal impulse responses, because the shocks in regime 2 of GMVAR model and in VAR model are contemporaneously correlated. Results of impulse response analysis are presented in Figure 3.

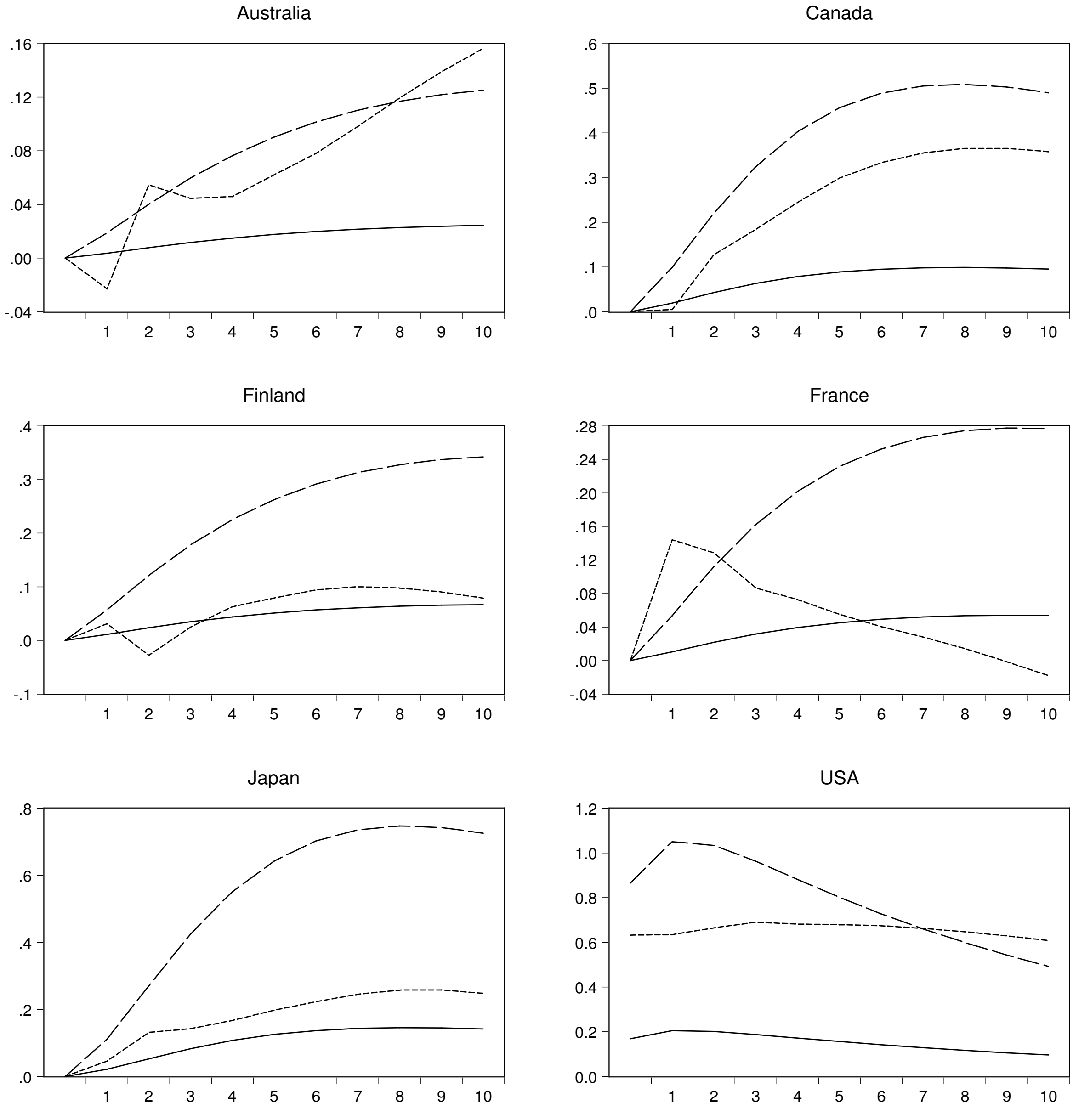


Figure 3. Orthogonal impulse responses of all countries to a unit change in the U.S. top 1% income share series based on regime 1 in GMVAR (solid line), regime 2 in GMVAR (dashed line) and VAR(2) (dotted line) models.

The different dynamics between regimes is clearly visible in Figure 3. In the (low inequality and low income fluctuations) regime 1, a shock to the U.S. series has a neg-

[13]The details on this estimated VAR(2) model is available upon request. The log-likelihood in GMVAR model is larger than in the VAR even though the VAR(2) model has 114 parameters and the GMVAR model has only 48. Thus, it is evident that the information criteria support the GMVAR model. Further, the quantile residual diagnostics strongly support the GMVAR model over the VAR(2) model.

ligible effect on series of other countries. For the USA, the effect is positive and decays slowly to zero. In the (high inequality and high income fluctuations) regime 2, a shock to the U.S. series has strong non-negligible effect on all countries. Because the autocorrelation structure is the same in both regimes, the differences are explained by the different error covariance matrices in regimes.

In the VAR model, the impact of the USA begins on level lower than in regime 2, but it is more persistent than in the GMVAR model. This might be explained by the fact that the largest root in the GMVAR model is 0.93 compared to 0.98 in the VAR model. Also, the impact of the U.S. on other countries is smaller in the VAR model than what is observed in regime 2. One may interpret that the VAR model represents a weighted average model over the two regimes, so its impact is also a weighted average. Therefore, the VAR model, e.g., underestimates the present-day impact of the U.S. on other countries. We consider the impulse responses of the GMVAR model to be more reliable, because the GMVAR allows for multiple equilibria whereas the VAR model allows only a unique equilibrium. That is, the GMVAR is in line with the observed nonlinear behavior of the top 1% income shares (Roine and Waldenström 2011; Piketty 2014).

To understand the overall effects of a shock in the U.S. series on the series of other countries, we compare the total accumulated impulse responses of the GMVAR model. In regime 1, the total accumulated effect is between 1 (in Australia) and 3 (in Japan). In regime 2 it is between 4 (in Australia) and 15 (in Japan). Accordingly, the impulse response analysis supports the idea that the income inequality in the USA drives income inequality in the other countries in our sample and that its effect is especially strong in the high inequality, high income fluctuations regime.

# 4 Discussion

The dynamics of income inequality seem to follow a joined path across our sample, and we can infer that income *equality* creates stability in the earned incomes of the top 1% (regime 1), while income *inequality* creates instability in the earned incomes of the same group (regime 2). Multivariate results show that the variance of income inequality is not only highly dependent across countries, but that income inequality in the United States is the driver of income inequality in other developed economies.

Results have three rather drastic implications. First, a shift from the first regime into the second regime indicates both a fall in the mean income and increase in the uncertainty (variance) of future income for the bottom 99%.[14] Mean income will fall, because the increase in the mean income share of the top 1% is greater than any conceivable short to medium term GDP growth. Thus, the high inequality regime is much more harmful for the bottom 99% income earners. For the 1%, however, there is a trade-off; in the second regime they receive more income, but with a greater risk than in the first regime. The welfare implications may thus be beneficial for the 1%, if there is an overall improvement of their relative incomes, but also negative, if the increase in risk offsets the possible gains in the relative income.

Second, Malinen (2012) and Herzer and Vollmer (2013) have found that the stochastic parts of income inequality and the GDP per capita have a long-run *equilibrium* relation. This indicates that larger stochastic fluctuations in the top 1% income share in the second regime translate to larger stochastic fluctuations in the GDP per capita creating macroeconomic instability. This finding is supported by Berg and Ostry (2011) who find that higher inequality is associated with shorter growth spells and *vice versa*.

Third, the level of inequality in the U.S. directly affects the future level of inequality in other developed countries. This level effect is also visible in how the regime changes occur: the U.S. has been driving the regime change in our sample in the 1950s and especially in the end of the 1980s. In addition, in the high inequality, high income fluctuations regime, the changes in the level of inequality in the U.S. are transmitted to all other countries through the covariance structure of that regime. This dynamic dependence between the level and the changes of inequality in the U.S. diminishes the control that individual countries have on their distribution of income.

These empirical findings naturally raise two important questions: what are the driving forces of regime switches and, more importantly, what is the role of the Unites States

[14]Top 1% income share has a high correlation with broader measures of income inequality (Atkinson *et al.* 2011; Leigh 2007), but it seems to have the biggest impact on the earnings of the middle-income families (Thompson and Leight 2013).

in these forces? Acemoglu and Robinson (2014) show that major changes in the top 1% income shares in Sweden and in South Africa have been associated with changes in economic and political institutions. Also in the U.S., institutional changes have affected the distribution of product. Campbell and Allen (2001) analyzed the average tax rate, progressivity of taxation and the population covered by taxes. They found four regimes describing the tax policies in the U.S. between 1916 and 1986:

1. 1916-1917, 1923-1933 (Symbolic)
2. 1918-1922, 1934-1940 (Fiscal crisis)
3. 1941-1953 (War making)
4. 1954-1985 (Macroeconomic stability)

Regimes from 1916 till 1941 were characterized by a low average tax rate and a low coverage of population subjected under the federal taxes. In the "War making" regime, the degree of progressivity of taxation, the average tax rate and the tax coverage increase dramatically. The "Macroeconomic stability" regime was characterized by high progressivity, a high average tax rate and a high coverage of taxation. This regime coincides with the low inequality, low income fluctuations regime found in the top 1% income share series of the U.S. (see Section 3.1) and other developed economies (see Section 3.2). Did the U.S. then drive the institutional change in other developed economies during the onset of this regime? This does not seem likely, because many countries adopted progressive income taxation and raised other taxes due to the war-related increase in government expenditures already in the 1940s (Galvin 1981; Reinhardt and Steel 2006; Kaneko 2009). The U.S. had also a smaller effect on the regime change in other countries in the 1950s (see Section 3.2.2). Liberal tax-lowering policies adopted under president Reagan's administration were likely to have a bigger influence on the resurgence of the high inequality, high income fluctuations regime in developed economies in the end of the 1980s. During that time, almost all OECD countries limited the number of personal income tax brackets and lowered their top statutory tax rates (Torres *et al.* 2012). Still, although the institutional change towards lower taxes originated from the U.S. in the 1980s, it cannot comprehensively explain the effect that the U.S. had on the income inequality in other developed economies during that period. Inequality in the U.S., for example, had the biggest effect on the levels of top 1% shares in Japan and in Canada (see section 3.2), but they pursued rather different tax policies than the U.S. in the 1970s and 1980s. During the tax reform of 1986-88, Japan adopted the value added tax (VAT) and raised several other taxes (Kaneko 2009). Canada adopted more liberal income taxation already in the 1970s before similar measures were introduced in the U.S. during the president Reagan's administration (Galvin 1981; Jacob 1985). Most importantly, adopting changes in taxation and other institutions relevant to income inequality usually takes longer than the one year which was the estimated lag length for the effect of the U.S. on the inequality of other countries (see Sections 3.2 and 3.2.2). Therefore, the dominance of the U.S. in the inequality in developed economies arises also on factors beyond institutional changes.

According to Piketty (2014), high income inequality in developed economies before the Second World War was mostly due to the larger share of income obtained from concentrated capital. Fluctuations in dividends and stocks added volatility in the share of income going to the top of the income earners. After the First World War, the global capital markets became highly integrated within a relative short period of time (Obstfeld and Taylor 1997), and by 1920's United States had accumulated the largest pool of private and public capital in the world (Bolt and Van Zanden 2013; Piketty 2014). In other words, the United States became the dominant power in capital markets after the First World War. The effect of the U.S. on the global capital markets was multiplied during the Great Depression which began in the U.S. and spread through the developed world. In the 1980's, U.S. began to liberalize its financial sector which led to a wave of financial liberalization in other developed economies (Jacob 1985; Stiglitz 2004). This increased the share of private capital to income, but the renewed increase in income inequality in developed economies was mostly caused by the rise in high wages. Two-thirds of the increase of income inequality that occurred in the U.S. after the mid-1970's is attributable to the increase in wages of the top 1% income earners, especially in the wages of top managers (Piketty 2014). This aggravated income inequality in other developed economies, because the wages of top managers in Europe (and elsewhere) need to keep up with the wages in the U.S. (Petit 2010). Top managers of the U.S. also exported higher salaries to other countries when they took up job offers around the world. The high volatility of incentives, bonuses and option prices (mostly through stock market fluctuations) of the top managers added to the increase in fluctuations of the top incomes during last few decades (Gottschalk and Moffitt 2009; Piketty 2014).

Therefore, it is likely that the economic and institutional change originating from the U.S. as well as globalization have driven the observed regime switches in the income inequality of developed economies. High income inequality, on the other hand, has contributed to higher variance in the share of income of the top earners through two interlinked channels. First, periods of high income inequality have been associated with periods of concentrated capital (Piketty 2014). Because financial capital has been an integral part of concentrated capital accumulation, the higher share of the volatile income from capital has increased the volatility of income of the top 1%. Second, during the latest era of globalization, price fluctuation of incentives, bonuses and options received by top managers have caused additional fluctuations in the top 1% income share series (Piketty 2014). Many of these developments in capital and labor markets have originated from the U.S., which has enhanced the influence of the United States on income inequality of other developed economies during the last 100 years.

# 5 Conclusions

In his recent path-breaking book, Piketty (2014) shows that the income inequality has followed an U-shaped path in many developed economies instead of the inverted-U shaped path hypothesized by Kuznets (1955). Results presented in this article add to this finding by showing that the level of inequality determines the characteristics of income distribution similarly as with inflation: it can be either equal and stable or unequal and volatile. Moreover, results indicate that changes in the dynamics of income inequality of developed economies are driven by changes in the inequality in the United States. All the countries in the sample were also found to currently reside in the high inequality, high income fluctuations regimes, where the effect of the U.S. is the strongest.

Our results yield some unpleasant policy implications. Because an increase in the mean share of the top 1% income earners in the high inequality, high income fluctuations regime is higher than any conceivable short to medium term growth of GDP, shift to this regime is harmful for the bottom 99% income earners. Larger fluctuations in the top 1% income share in the high inequality, high income fluctuations regime also translate to larger stochastic fluctuation in the GDP per capita, because the stochastic parts of income inequality and the GDP per capita have been found to have a joint *equilibrium* relation (Malinen 2012; Herzer and Vollmer 2013). This combination makes poor and middle-income households bearers of the costs of income inequality in more than one way: increasing income inequality lowers their share of the total income disproportionately and increases the uncertainty of their future income.[15] The attempts of sovereign nations to reduce the costs associated to income inequality are also diminished by the dependence of the inequality on that in the U.S.

The United States has dominated the capitalist word since the beginning of the 20th century. According to our results, this holds also for the dynamics of income distribution that seem to be more integrated across developed economies than previously thought. This dominance is likely to result from the economic and institutional change that has originated from the U.S. In addition, globalization in the form of integration of capital and job markets has been likely to contribute to the convergent increases in income inequality in developed economies between the World Wars and during the last few decades. Due to the continuing integration of the world economy, it is likely that the dynamics of income inequality are destined to become even more interrelated between developed economies, or globally, in the future.

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[15]In addition, the inequality may enforce itself in the high inequality, high income fluctuations regime because stronger business cycle fluctuations can exacerbate income inequality (Ashley 2007; Fawaz *et al.* 2012).

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# Appendix: Details of regime change

Figure A1 depicts the contours of the mixing weight $\hat{\alpha}_{1,t}$ ($t = 1954, 1955, 1956$) as a function of lagged observations $y_{t-1,USA}$ and $y_{t-1,i}$, where $i$ is each of the other five countries. Because the mixing weight $\hat{\alpha}_{1,t}$ is a function of the 12-dimensional vector $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$, we have to condition it on other values in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$ by fixing these values equal to the observed values in the data. Thus, for each $t$, the conditioning set changes and this may cause large changes in the shape of $\hat{\alpha}_{1,t}$. In each plot, an arrow indicates the shift from $(y_{t-1,USA}, y_{t-1,i})$ into $(y_{t,USA}, y_{t,i})$. These arrows highlight the effect the changes in income inequality in the U.S. have on the regime changes. The change from regime 2 ("high income inequality, high income fluctuations") into regime 1 ("low income inequality, low income fluctuations") occurs between 1954-1956, because $\hat{\alpha}_{1,1954} = 0$, $\hat{\alpha}_{1,1955} = 0.65$ and $\hat{\alpha}_{1,1956} = 0.82$. In the first column of Figure A1, one observes that the movement is towards the elliptical region where the probability of regime 1 is higher. Note that in all subfigures the minor axes of the ellipses are parallel and in the direction of $y_{t-1,USA}$. Thus, the changes in the U.S. series have the strongest effect on the probability of regime 1. As the consecutive observations are close to each other (in the U.S. series in particular), the observation remains in the area where the probability of regime 1 is high. Thus, as long as the changes in all the series remain small, the 6-dimensional series is in regime 1 with probability over 0.96 or higher.

Figure A2 depicts the contours of the mixing weight $\hat{\alpha}_{2,t}$ ($t = 1987, 1988, 1989$) as a function of lagged observations $y_{t-1,USA}$ and $y_{t-1,i}$, where $i$ is each of the other five countries. Similarly to Figure A1, we condition on the other values in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$ by fixing these values equal to the observed values in the data and the arrows indicate the shift between consecutive observations. The change from regime 1 into regime 2 occurs between 1987-1988, because $\hat{\alpha}_{2,1987} = 0.10$ and $\hat{\alpha}_{2,1988} = 1.00$. In the first column of Figure A2, the movement is away from the region where the probability of regime 1 is high into the region where the probability of regime 2 is high. This movement is caused by the large increase in the U.S. series, which then increases the probability of regime 2 (2nd column). Note that there is also a large increase in the Australian series,

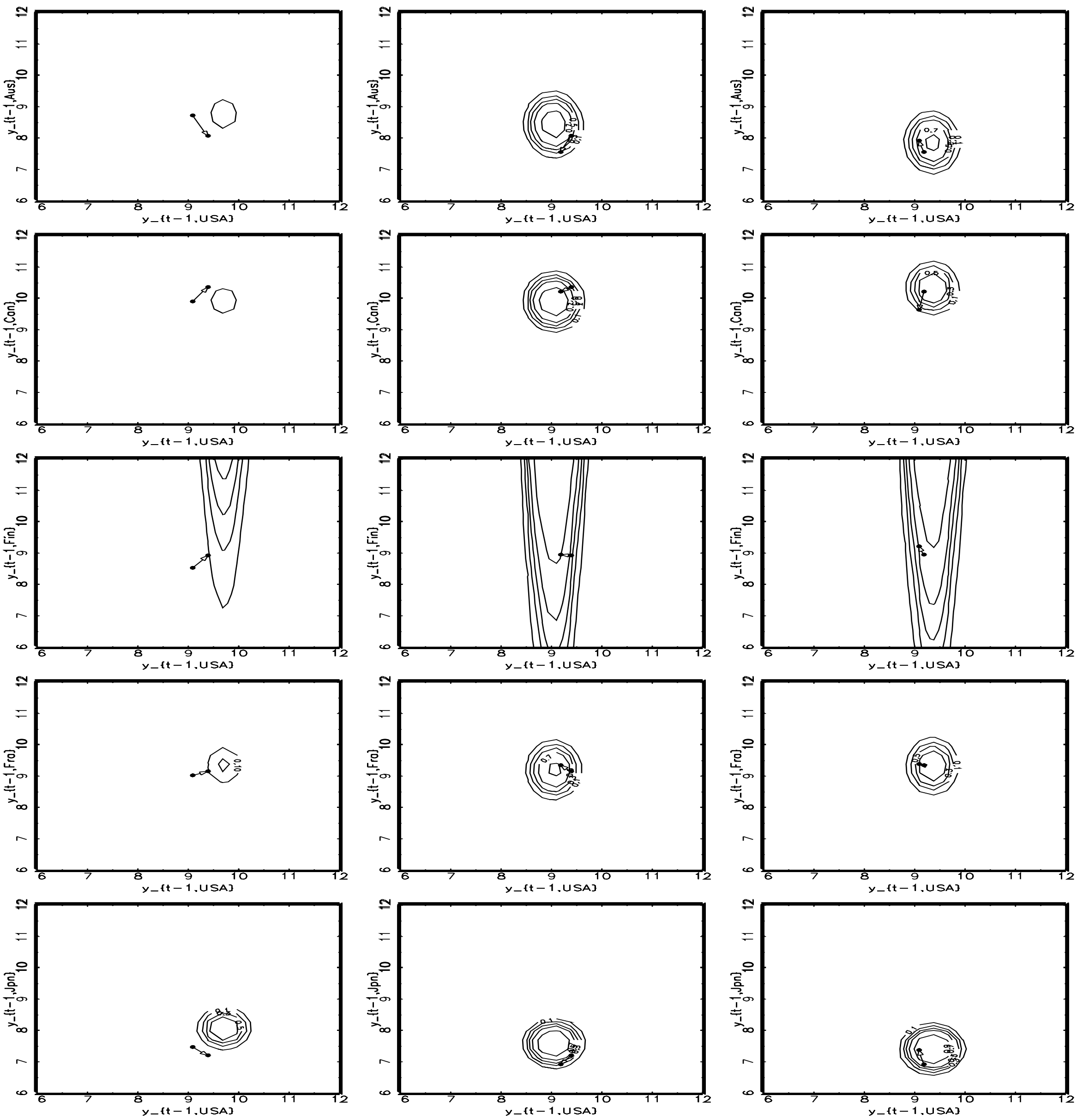

Figure A1: Contour plots of the mixing weights $\hat{\alpha}_{1,t}$ as a function of $(y_{t-1,USA}, y_{t-1,i}), i = (Aus, Can, Fin, Fra, Jpn)$ with the rest of the values fixed (for each $i$) in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$. The fixed values in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$ correspond to observations of 1952 and 1953 (left), 1953 and 1954 (middle), and 1954 and 1955 (right) and from top to bottom $i = Aus, Can, Fin, Fra, Jpn$. The arrows point from observation $(y_{1953,USA}, y_{1953,i})$ into observation $(y_{1954,USA}, y_{1954,i})$ (left), from observation $(y_{1954,USA}, y_{1954,i})$ into observation $(y_{1955,USA}, y_{1955,i})$ (middle),and from observation $(y_{1955,USA}, y_{1955,i})$ into observation $(y_{1956,USA}, y_{1956,i})$ (right).

but this increase does not cause the changes in regimes in other countries as only the lagged value of US series is needed in the multivariate model of $y_{t-1,i}$ for all $i$.[16] As the consecutive observations continue to increase (particularly in the U.S. series), the observations move horizontally away from the area where the probability of regime 1 is high. The probability of regime 1 reduces to 0 very quickly as there are no visible

[16]This is also checked using other graphs not reported here.

contours in the third column of Figure A2 except in the plots for France (the contours of regime 3). Thus, as the U.S. series begins the fast growth, the 6-dimensional series moves into regime 2 with probability 1.

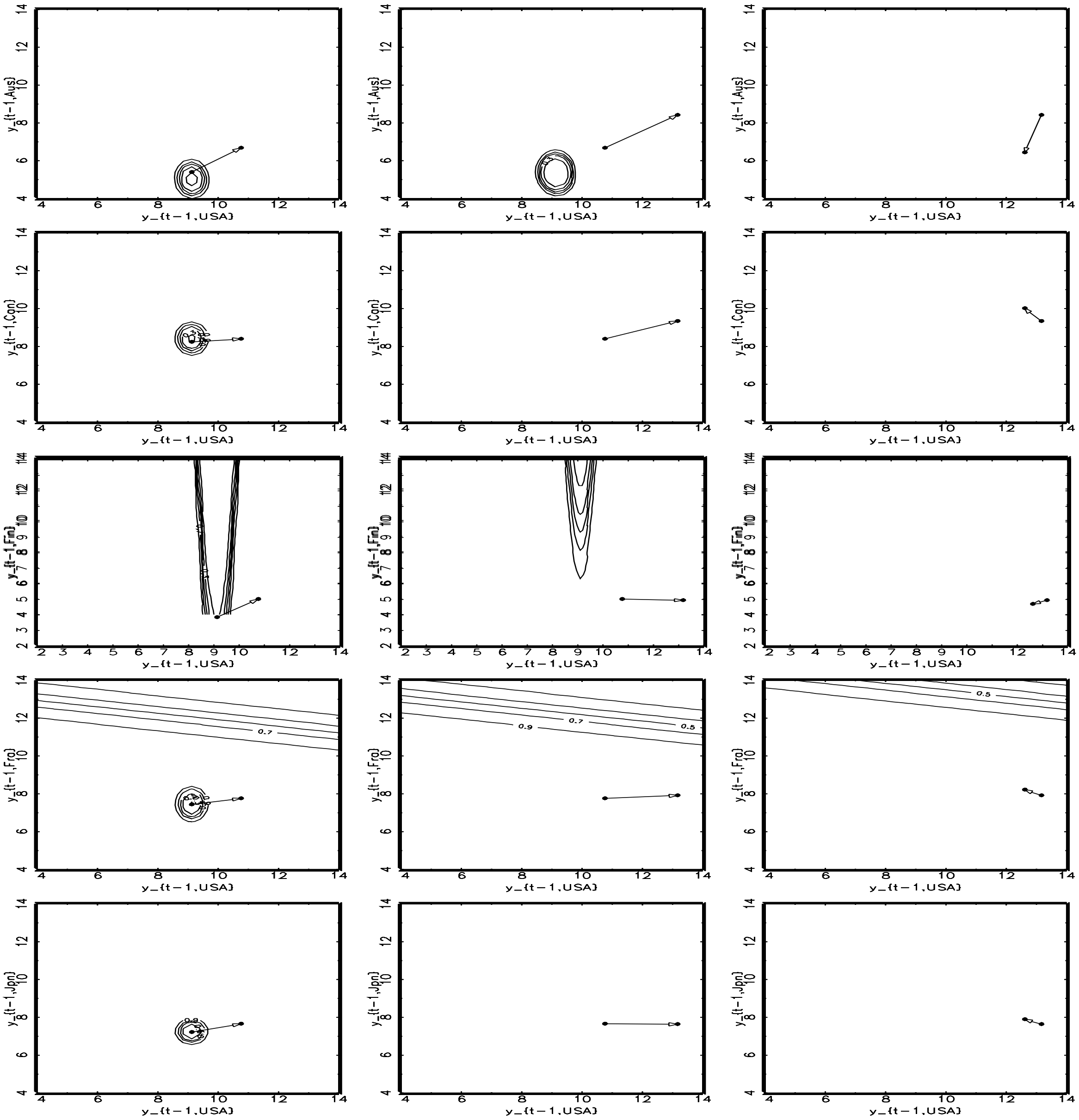

Figure A2: Contour plots of the mixing weights $\hat{\alpha}_{2,t}$ as a function of $(y_{t-1,USA}, y_{t-1,i}), i = (Aus, Can, Fin, Fra, Jpn)$ with the rest of the values fixed (for each $i$) in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$.The fixed values correspond to observations of 1985 and 1986 (left), 1986 and 1987 (middle), and 1987 and 1988 (right) and from top to bottom $i = Aus, Can, Fin, Fra, Jpn$**.** The arrows point from observation $(y_{1986,USA}, y_{1986,i})$ into observation $(y_{1987,USA}, y_{1987,i})$ (left), from observation $(y_{1987,USA}, y_{1987,i})$ into observation $(y_{1988,USA}, y_{1988,i})$ (middle),and from observation $(y_{1988,USA}, y_{1988,i})$ into observation $(y_{1989,USA}, y_{1989,i})$ (right).

Figure A3 depicts the contours of the mixing weights $\hat{\alpha}_{1,t}$ $(t = 1954, 1955, 1956)$ and $\hat{\alpha}_{2,t}$ $(t = 1987, 1988, 1989)$ as a function of lagged observations $y_{t-1,USA}$ and $y_{t-2,USA}$.

Again, we condition on the other values in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$ by fixing these values equal to the observed values and use the arrows to indicate the shift from $(y_{t-1,USA}, y_{t-2,USA})$ into $(y_{t,USA}, y_{t-1,USA})$. The upper panel of Figure A3 depicts change from regime 2 into regime 1 between 1954-1956. We observe that the changes in the U.S. series become notably smaller. The lower panel depicts the change from regime 1 into regime 2 between 1987-1988. The rapid increase in the U.S. series begins at 1987 and accordingly the probability of regime 2 quickly jumps into 1. Lastly, the small changes in the U.S. series lead the 6-dimensional series into the low variance regime 1 whereas large changes lead the 6-dimensional series into the high variance regime 2.

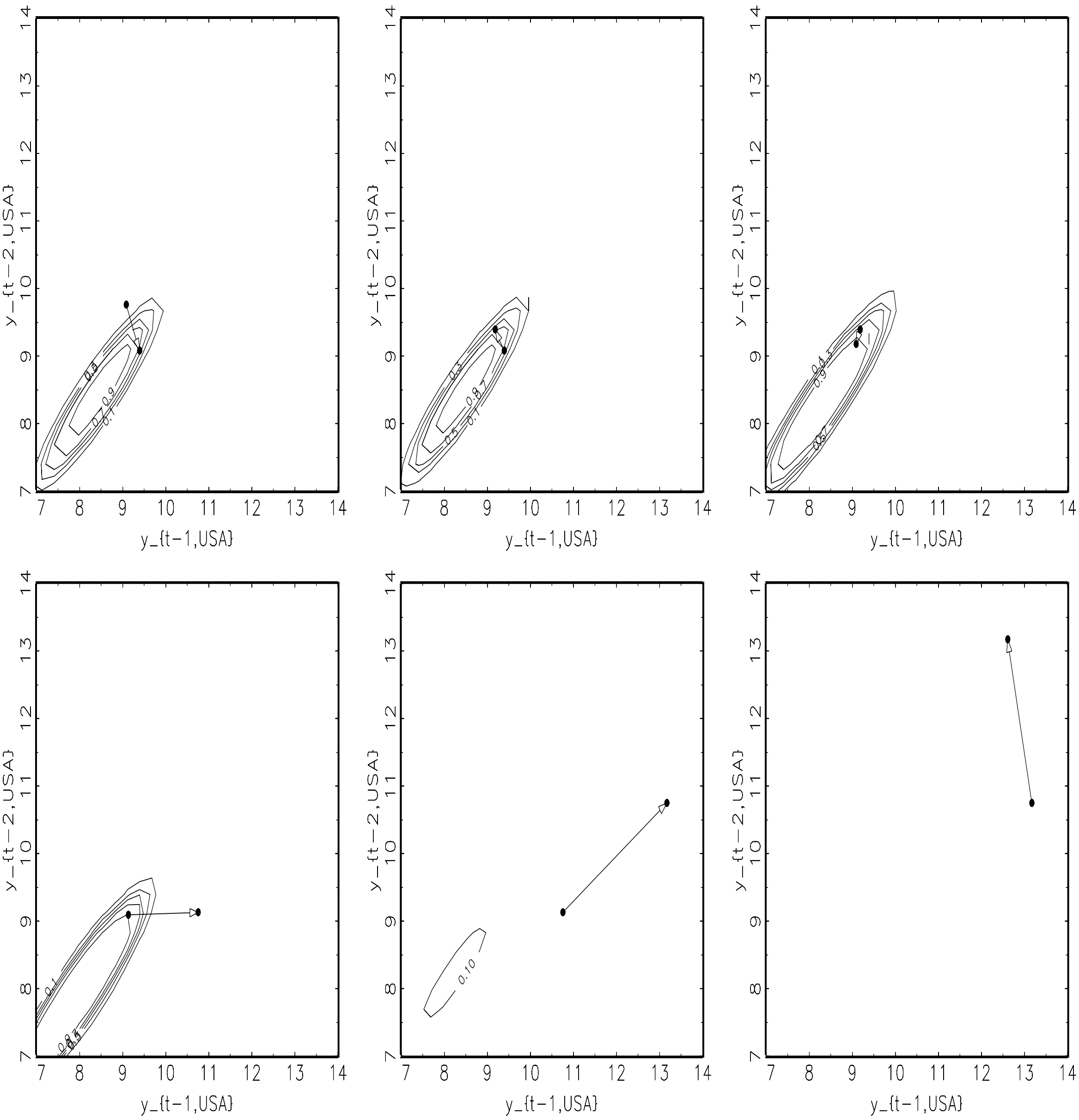


Figure A3: **Upper panel:** Contour plots of the mixing weights $\hat{\alpha}_{1,t}$ as a function of $(y_{t-1,USA}, y_{t-2,USA})$ with the rest of the values fixed in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$.These fixed values are chosen to match the observations of 1952 and 1953 (left), 1953 and 1954 (middle), and 1954 and 1955 (right). The arrows point from observation $(y_{1953,USA}, y_{1952,USA})$ into observation $(y_{1954,USA}, y_{1953,USA})$ (left), from observation $(y_{1954,USA}, y_{1953,USA})$ into observation $(y_{1955,USA}, y_{1954,USA})$ (middle),and from observation $(y_{1955,USA}, y_{1954,USA})$ into observation $(y_{1956,USA}, y_{1955,USA})$ (right). **Lower panel:** Contour plots of the mixing weights $\hat{\alpha}_{2,t}$ as a function of $(y_{t-1,USA}, y_{t-2,USA})$ with the rest of the values fixed in $(\mathbf{y}_{t-1}, \mathbf{y}_{t-2})$.These fixed values are chosen to match the observations of 1985 and 1986 (left), 1986 and 1987 (middle), and 1987 and 1988 (right). The arrows point from observation $(y_{1986,USA}, y_{1985,USA})$ into observation $(y_{1987,USA}, y_{1986,USA})$ (left), from observation $(y_{1987,USA}, y_{1986,USA})$ into observation $(y_{1988,USA}, y_{1987,USA})$ (middle),and from observation $(y_{1988,USA}, y_{1987,USA})$ into observation $(y_{1989,USA}, y_{1988,USA})$ (right).